Factorization in Deep Neural Networks - Part 2

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Course organisation

Sessions

1. Deep Learning and Transfer Learning,
2. Quantization,
3. Pruning,
4. Factorization,
5. Fact. pt.2 : Operators and Architectures,
6. Distillation,
7. Embedded Software and Hardware for DL.
8. Presentations for challenge.

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General principle

Complexity of 2D Convolutions

$N_{ops} = H_{out} \cdot W_{out} \cdot h \cdot w \cdot D_{in} \cdot D_{out}$
with kernel size (h, w), D_{in} the number of input feature maps, D_{out} the number of output feature maps of height H_{out} and width W_{out}.

To reduce the number of parameters, we can :

- Reduce the size of kernels
- Reduce the number of feature maps

Different strategies :

- Decompose kernels
- Depthwise Separable Convolutions
- Grouped Convolutions

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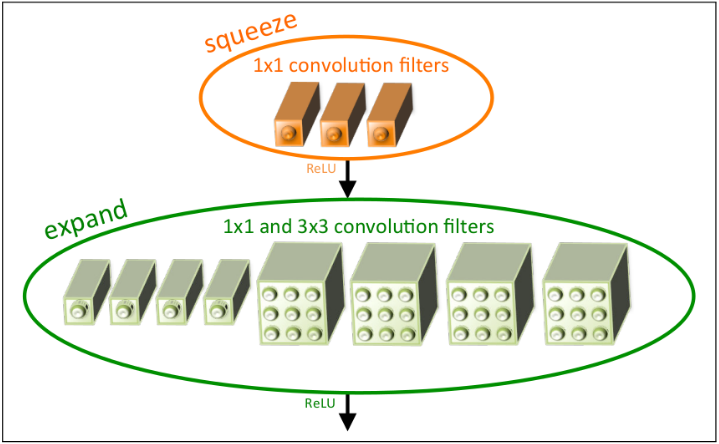
Decomposing kernels

Assuming $D_{in} = D_{out}$, decompose (h, w) kernel by $(h, 1)$ and $(1, w)$:
$N_{ops} = h.1.D_{in}^2 + 1.w.D_{in}^2 = (h + w).D_{in}^2$
with kernel size (h, w), D_{in} input and out number of feature maps.

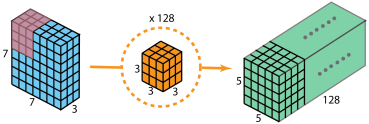
Introducing the Fire Module



Iandola et al. 2016, `https://arxiv.org/abs/1602.07360`

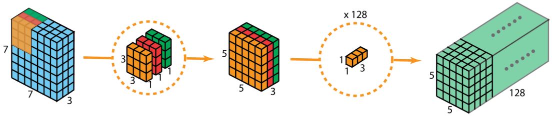
Depthwise serparable convolutions

Instead of learning parameters that recombine all input feature maps to compute each output feature map:



$$N_{mul} = H_{out} \cdot W_{out} \cdot h \cdot w \cdot D_{in} \cdot D_{out}$$
$$N_{mul} = 5 \cdot 5 \cdot 3 \cdot 3 \cdot 3 \cdot 128 = 86400$$

One can separate the operations into two steps:

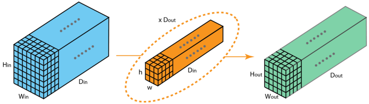


$$N_{mul} = H_{out} \cdot W_{out} \cdot h \cdot w \cdot D_{in} \cdot 1 + h \cdot w \cdot 1 \cdot 1 \cdot D_{in} \cdot D_{out}$$
$$N_{mul} = 5 \cdot 5 \cdot 3 \cdot 3 \cdot 3 \cdot 1 + 5 \cdot 5 \cdot 1 \cdot 1 \cdot 3 \cdot 128 = 10275$$

https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

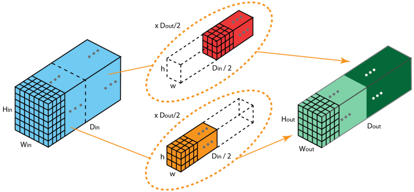
Grouped Convolutions

Instead of learning parameters that recombine all input feature maps to compute each output feature map:



$$N_{mul}^{N} = H_{out} \cdot W_{out} \cdot h \cdot w \cdot D_{in} \cdot D_{out}$$

One can divide the kernels into multiple groups:



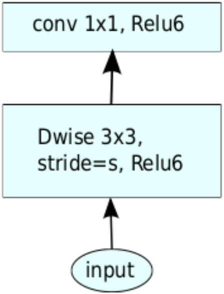
$$N_{mul}^{G} = H_{out} \cdot W_{out} \cdot h \cdot w \cdot \frac{D_{in}}{2} \cdot \frac{D_{out}}{2} + H_{out} \cdot W_{out} \cdot h \cdot w \cdot \frac{D_{in}}{2} \cdot \frac{D_{out}}{2}$$

$$N_{mul}^{G} = \frac{N_{mul}^{N}}{2}$$

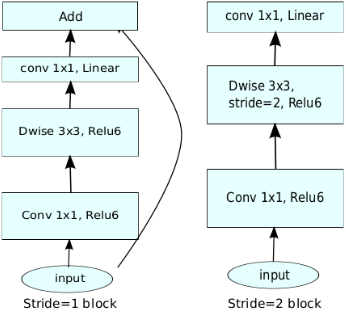
https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

MobileNet

MobileNetV1



MobileNetV2



`https://arxiv.org/abs/1704.04861` and `https://arxiv.org/abs/1801.04381`

MobileNet

Accuracy obtained on ImageNet

Network	Accuracy(%)	Params (M)
SqueezeNet	57.5	1.24
MobileNetV1	70.6	4.20
MobileNetV2	72.0	3.40

https://arxiv.org/abs/1704.04861 and https://arxiv.org/abs/1801.04381

Introducing Shift Attention Layer

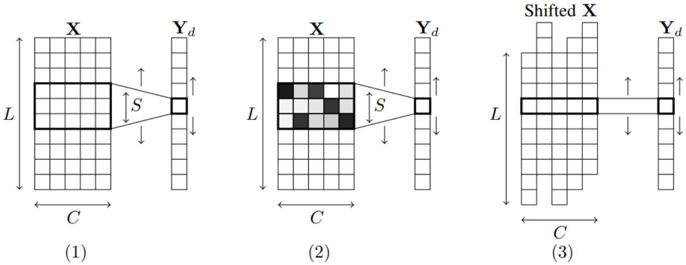


Figure 1: Overview of the proposed method: we depict here the computation for a single output feature map d, considering a 1d convolution and its associated shift version. Panel (1) represents a standard convolutional operation: the weight filter $\mathbf{W}_{d,\cdot,\cdot}$ containing SC weights is moved along the spatial dimension (L) of the input to produce each output in $\mathbf{Y}_d$. In panel (2), we depict the attention tensor $\mathbf{A}$ on top of the weight filter: the darker the cell, the most important the corresponding weight has been identified to be. At the end of the training process, $\mathbf{A}$ should contain only binary values with a single 1 per slice $\mathbf{A}_{d,c,\cdot}$. In panel (3), we depict the corresponding obtained shift layer: for each slice along the input feature maps (C), the cell with the highest attention is kept and the others are disregarded. As a consequence, the initial convolution with a kernel size S has been replaced by a convolution with a kernel size 1 on a shifted version of the input $\mathbf{X}$. As such, the resulting operation in panel (3) is exactly the same as the shift layer introduced in Wu et al. [2017], but here the shifts have been trained instead of being arbitrarily predetermined.

Hacene et al. 2019, `https://arxiv.org/abs/1905.12300`

Alternatives to Convolution

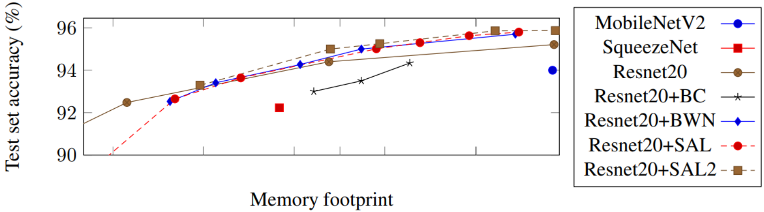


Figure 7: Evolution of accuracy when applying compression methods on different DNN architectures trained on CIFAR10.

Hacene et al. 2019, `https://arxiv.org/abs/1905.12300`